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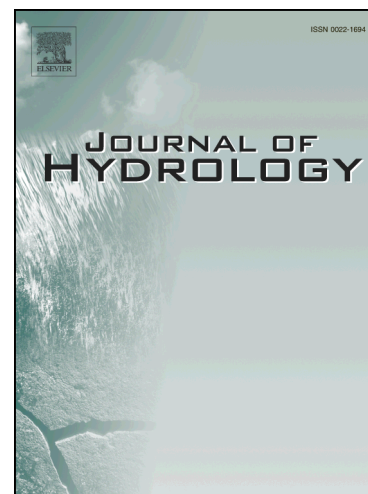
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PREDICTING WATER ALLOCATION TRADE PRICES USING A HYBRID ARTIFICIAL NEURAL NETWORK-BAYESIAN MODELLING APPROACH

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Key Points

- Artificial Neural Network (ANN) approaches were used to model and predict water trading prices in the Murry Irrigation area, Australia.
- Prices forecast using hybrid ANN-Bayesian modelling showed greater agreement with actual water prices.
- Water security allocations, cereal and meat prices were significant determinants of future water trading prices.

Abstract: This paper proposes an integrated (hybrid) Artificial Neural Network-Bayesian (ANN-B) modelling approach to improve the accuracy of predicting seasonal water allocation prices in Australia's Murry Irrigation Area, which is part of one of the world's largest interconnected water markets. Three models (basic, intermediate and full), accommodating different levels of data availability, were considered. Data were analyzed using both ANN and hybrid ANN-B approaches. Using the ANN-B modelling approach, which can simulate complex and non-linear processes, water allocation prices were predicted with a high degree of accuracy ($R_{BASIC} = 0.93$, $R_{INTER} = 0.96$ and $R_{FULL} = 0.99$); this was a higher level of accuracy than realized using ANN. This approach can potentially be integrated with online data systems to predict water allocation prices, enable better water allocation trade decisions, and improve the productivity and profitability of irrigated agriculture.

Keywords: Water allocation prices, Artificial Neural Network model, hybrid Artificial Neural Network-Bayesian model, water trade, price prediction.

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1. Introduction

Existing irrigated agriculture will come under intense pressure due to shifts in weather patterns, changes in rainfall events and increasingly varied hydrological regimes (IPCC, 2012). These changes will cause increased agricultural water demand, especially during dry years. Most farm water use and management decisions are based on seasonal water allocations and the opportunity cost of water use (Randall, 1981). Water markets, where they exist, provide farmers with clear opportunity cost and price signals that can potentially improve the economic efficiency of water use in terms of higher profit per hectare and per megalitre of water, given limited water availability and higher inter-temporal risk (Qureshi *et al.*, 2010, 2013). This is because, in the absence of distortions, water markets allocate water to equalize the marginal benefits from its use across sectors/users and to magnify social welfare (Skurray, 2012). A perfectly competitive market, in equilibrium, will result in water prices equal to the value of its marginal product, while water prices generated under distortionary (e.g. political, institutional, infrastructural, informational) constraints may result in inefficient resource use at the margins (Chong *et al.*, 2006). Access to water markets can also assist agricultural water users in their adjustment to uncertainty through participation in water allocation trade, consistent with their risk management and commodity options (Brennan, 2004). Thus, improved water allocation price information may lead to more efficient use of increasingly scarce and expensive water resources, resulting in increased farmer returns on investment and positive social welfare outcomes.

Two types of water product are generally traded: water allocations (also known as seasonal or temporary trade) and water entitlements (also known as permanent trade). A water entitlement is defined as a perpetual or ongoing right to a share of water from a specified consumptive pool, while a water allocation is the specific volume of water allocated to water access entitlements in any given season (Wheeler *et al.*, 2014). It is important to distinguish in the literature between studies that examine trade activity (e.g. Loch *et al.* 2012), price elasticity (e.g. Wheeler *et al.* 2008) and trade price drivers. Trade price drivers for water allocation products are the focus of this paper. In the United

Sates, for example, prices can be driven by the volume of water allocations traded between urban and agricultural users (Colby et al. 1993); although since >95% of water trades in Australia are agricultural in nature this may be of lesser concern (Bjornlund and Rossini 2007). Important drivers of Australian water allocation trade prices typically include: water scarcity (abundance) as a consequence of drought (flooding) events which also impact on rainfall and evaporation variations (Bjornlund 2004; Bjornlund and Rossini 2005); seasonal allocation announcements on the back of annual rainfall outcomes and water manager assessments (Bjornlund 2002, 2003; Peterson et al. 2004; Brennan 2006); risk averse attitudes held by farmers or different industries (Brennan 2006; Brooks and Harris 2008); the substitutability of water for other farming inputs such as feed (Bjornlund 2003; Peterson et al. 2004); spatial or physical trade restrictions within and between different areas (Gardner and Miller 1983; Brennan 2006); inefficient trade rule and/or price discovery processes (Brennan 2006); cost-differences between water allocation and other trade products (Brooks and Harris 2008); the degree to which water is required to preserve capital-intensive production systems (Bjornlund and Rossini 2005; Adamson et al. 2017); and the bargaining strength of different traders in the market (Gardner and Miller 1983) or the presence of strategic bidding behaviour in the form of excessive demand variability (Oczkowski 2005).

Despite this rich list of water allocation price drivers in a market, Australian water allocation prices typically show considerable temporal variation and are generally negatively correlated with supply; that is, prices rise with decreasing availability (Bjornlund and Rossini, 2007). Hence, during periods of drought, which are common in many contexts around the world, low opening and/or persistently constrained volumetric allocations create significant water allocation price uncertainty for farmers. For instance, in 2006–07 at the height of the ‘Millennium drought’ (1996–2010) in Australia, volumetric water allocations for some regions and property right categories in the Murray–Darling Basin (MDB)—one of the world’s largest interconnected water markets—were announced at 0% of total entitlement; as a consequence, water allocation prices were far higher than in previous years (Kirby et al., 2012). However, in such atypical years, risk averse irrigators may also pay a price

premium early in a season to reflect supply uncertainty and a risk premium above the expected water value, which would be likely to decline monthly over the season as a rule (Brennan 2006). So if the capacity of different water users to forecast allocation water prices can be improved, this may increase their respective gains from trade (and/or decrease the risk premiums incurred) by irrigators over the course of a season.

1.1 The value of water allocation price predicting

Future increased climatic and hydrological variability will significantly impact on future water allocation supply and pricing, resulting in a considerable interest in water market activity and governance emphasis on agricultural efficiency in regions such as the MDB (Adamson et al. 2017). These risks and impacts may be mitigated by more accurate forecasts of future water allocation prices at the start or end of cropping seasons, improving farmer capacity to make more efficient cropping decisions and increase total farm profitability. In recognition of this, the Australian government invested \$460 million over ten years to improve availability and access to water information for better risk management by irrigators, environmental managers and policymakers, while a further \$56 million was also invested in more transparent national market information for users (Horne, 2012). Improved water allocation price forecasts will also allow buyers and sellers to develop profitable cropping plans, in advance, based on soil types, irrigation systems, water availability and future climate and market outlooks. Studies have indicated that water allocation trading has been instrumental in enabling irrigators to better manage drought, debt levels and farm operations by selling/buying water allocations (National Water Commission, 2010; Wheeler et al. 2014). For example, rice producers in the Murray Irrigation Area were able to sustain income during drought years when volumetric allocations were extremely low (<10%) by selling their water allocations through markets (Mushtaq et al. 2013; National Water Commission, 2010).

Improved water allocation price forecasts will enable both buyers and sellers of water to make water market decisions with greater certainty with regard to the optimal use of their water assets, thereby buffering farm income when water allocations are constrained. Water allocation price forecasts several months in advance will allow irrigators to make early informed decisions, based on anticipated crop net production value (\$/megalitre [ML], where 1ML = 810.6 acre-feet), regarding participating in water markets as either buyers or sellers. If the likely water allocation price exceeds the crop net production value, an irrigator might maximize farm income by reducing the crop area and selling water. However, if the likely water allocation price is less than potential crop net production values, buying water could enable a larger area of crop to be planted than would otherwise be possible (i.e. in the absence of water market information and land area constraints). Although Brennan (2008) suggests that losses in economic value associated with reduced reliability offset any potential gains from trade in the MDB, Grafton et al. (2012) estimate that total gains from trade in the MDB are worth hundreds of millions of dollars per annum. Modelling by the National Water Commission (2012) also estimated that MDB production during the drought period 2006–07 to 2010–11 was AU\$4.3 billion higher with water allocation trade and that expanded access to water allocation trade had reduced drought impacts from AU\$11.7 to AU\$7 billion over that same period. Khan et al. (2010) showed the benefits of water allocation trade using a hypothetical mixed farming system in the MDB. The results indicated that, at lower water allocation prices (<\$200/ML) associated with higher volumetric allocation levels, the irrigator could maximize farm income (\$374,825) by buying additional water allocation (334ML) through the market, given the farm biophysical and economic constraints. However, at higher water allocation prices (>\$630/ML) due to low volumetric allocation levels, the irrigator was better off reducing the area of irrigated crop and selling water allocation (425ML), potentially making \$348,500. Finally, Adamson et al. (2017) highlight the differences in water allocation trade strategies across annual and perennial producers, and the theoretical constructs underpinning farmer responses to a given supply of water, and this informs the approach adopted in this paper.

While the benefits of improved water allocation demand (price) predicting accuracy may be mixed depending on an agricultural water users' operation and accuracy requirements (Zareipour *et al.*, 2010), improved capacity by agricultural water users to make timely annual selections of annual commodities and/or adopt risk management arrangements with more accurate water allocation price predictions should create economic welfare and improved marginal water use outcomes (Dziegielewski, 2011). Further, the provision of effective information and institutional platforms to support water allocation price prediction has not matched market development (Wheeler, 2016; Wheeler *et al.*, 2017; Cui and Schreider, 2009); this is particularly critical given the monthly price variation typically evident in water allocation price reporting (e.g. National Water Commission, 2013).

1.2 Prediction approaches

Predicting water allocation prices faces significant challenges due to the complexity of the relationships involved. Typically, water resource researchers have used conventional modelling techniques such as regression analysis, time series analysis and autoregressive moving averages (Jain *et al.*, 2001). More recently, due to the inherent complexity in modelling water resources, the non-linearity of water allocations, and the difficulties of building linear relationships between water allocations for winter and summer periods using conventional models, researchers have adopted the artificial neural network (ANN) method to estimate these complex factors (Khan *et al.*, 2005; Kingston *et al.*, 2005; Maier *et al.*, 2010; Sakaa *et al.*, 2013; Liu *et al.*, 2014; Li *et al.*, 2015; Wu *et al.*, 2014). ANN models emulate the properties of biological nervous systems for adaptive learning from historical data, using patterns in the data to predict the future (Nowlan and Hinton, 1992; Cancelliere *et al.*, 2002). They can be trained to predict outputs through parallel processing of multiple-independent inputs (Haykin, 1999). From a review of 43 papers on the topic, Maier *et al.* (2010) concluded that ANNs provide a useful tool for the prediction and forecasting of water resource variables. The neural network approach is also commonly accepted as the best modelling method currently available, particularly for economic price forecasting, as it can capture nonlinearities in the

system (Lawrence, 1997; Smith and Mason, 1997; Khan et al., 2010). Neural networks are non-linear parallel computational techniques which are flexible and offer better fitting outputs with regard to the training data, than linear models. However, an error of over-fitting can occur during neural network training with a large number of parameters in the new data (Srivastava *et al.* 2014).

Bayesian approaches, based on Bayes' rule, incorporate a likelihood function, which calculates the probability of the observed data conditional on the values of other parameters in the dataset (MacKay, 1992; Robert, 2007). Hence, a hybrid ANN-Bayesian modelling approach should enable a more probabilistic interpretation of the behaviour of a complex dataset. Kingston et al. (2005) used a Bayesian model selection (BMS) method based on Markov Chain Monte Carlo (MCMC) approach applied to a salinity forecasting case study. In contrast to a solely neural network model, the ANN-B model can solve the over-fitting problem using Bayesian regularization (MacKay, 1992). Ideally, the network training algorithm will adopt a Bayesian regularization back-propagation approach to update the weight and bias values according to Levenberg-Marquardt optimization.

In this paper, we investigate the potential for a hybrid ANN-Bayesian (ANN-B) approach to further improve model accuracy in water allocation price prediction in a case study water market to potentially increase efficient agricultural water (re)allocation at the margin and improve gains from water allocation trade. Specifically, we forecast monthly New South Wales (NSW) Murray Irrigation Area water allocation prices using both Artificial Neural Network (ANN) and hybrid Artificial Neural Network-based Bayesian (ANN-B) modelling approaches. Our results indicate that, while ANN models can accurately predict water allocation prices with a less than 5% error margin on a monthly basis over the period 1999–2015, a hybrid ANN-B model provides greater consistency between actual and forecast prices, suggesting improved capacity to predict water allocation prices and potential for greater economic gains through water allocation trade. The paper contributes to the water market literature by providing a monthly water allocation price predicting model that can be used to

anticipate water allocation prices across the cropping season; this information can be used in decision-making to potentially improve the gains from trade.

2. Methods

2.1 Study area

The study area for the paper is the Murray Irrigation Area (MIA), located in the southern MDB (Figure 1). Irrigation farming activity in this region accounts for 7.7% of total MDB irrigation water use (MIL, 2006). The land-use pattern in the Murray Irrigation Area shows the diverse nature of agriculture in the region (see supplementary Table S1). In the MIA, the average level of allocation made against general security entitlements¹ was about 124% before restrictions on water extraction were imposed in 1994–95 with the imposition of ‘the Cap’², falling to 65% after this (see supplementary Figure S1). The region has an annual bulk water entitlement of 1,479,000ML (see supplementary Table S2) and is generally a net importer of water facilitated through the water market. The local privately-owned irrigation company, Murray Irrigation Limited (MIL), provides water from their bulk holding to about 2,416 landholdings (total land area of 748,000 ha), as well as urban water supply to eight local rural towns.



Figure 1: Murray Irrigation Area, Australia. (Source: <http://www.murrayirrigation.com.au/>).

Markets for water have a lengthy history in Australia, and are now reasonably well established in the southern MDB (Loch *et al.*, 2013). Relatively low transaction costs associated with water allocation trade mean that markets provide a useful risk-mitigation strategy for MDB irrigators, particularly during droughts (Wittwer and Griffith, 2011). Since 1994–95, when the Murray Darling Basin Commission imposed the Cap limit on total water diversions, water trading activity has gradually increased. The volume of water traded throughout the MIA has also risen steadily in response to periodic variations in seasonal water volumetric allocations. For instance, at the height of the Millennium Drought, some 95,000ML of water allocations worth AU\$4.3 million was traded between August 2005 and May 2009 (MIL, 2006), and decreases in agricultural production and net income were lower than expected under the counterfactual, highlighting the value of water trade (Wittwer and Griffith, 2011).

2.2. Analytical framework

The findings of our study, whilst not specifically transferrable to other markets around the MDB or globally, provide a useful step toward identifying the value of price prediction for farmers and possible gains from trade. As outlined above, water allocation prices are determined by various supply and demand factors. These include seasonal rainfall conditions, volumetric allocations, current output, commodity prices (Wheeler *et al.*, 2008, Bjornlund and Rossini, 2007, Loch *et al.* 2012) and farmers' socio-economic characteristics and type of farm (Wheeler *et al.* 2010).

Three models are proposed to forecast water allocation prices; these are referred to as the basic, intermediate and full models (Khan *et al.*, 2010) described below:

- (i) *Basic model* is designed with the weighted average price (A\$ ML⁻¹) of water allocations from the current month to 3 months earlier, as follows:

$$P_{W(m+1)}^T = f\left(P_{W(Avg.(m,m-1,m-2))}^T, P_{W(Avg.(m-1,m-2,m-3))}^T\right) \quad (1)$$

- (ii) *Intermediate model* is based on the weighted average price (A\$ ML⁻¹) of water allocations, the average Standardized Precipitation Index (SPI) (McKee *et al.*, 1993) and the average general security water volumetric allocation (percent) from the current month to four months earlier:

$$P_{W(m+1)}^T = f\left(P_{W(Avg.(m,m-1,m-2))}^T, P_{W(Avg.(m-1,m-2,m-3))}^T, SPI_{Avg.(m-1,m-2,m-3)}^T, A_{Avg.(m,m-1,m-2)}^T, A_{Avg.(m-1,m-2,m-3)}^T, A_{Avg.(m-2,m-3,m-4)}^T\right) \quad (2)$$

In this model, drought is a more important factor, significantly impacting water allocation trade price and agricultural production over time. The SPI is used to determine the rarity of a drought at a given time scale for historic rainfall data.

- (iii) *Full model* is designed for the current month and the previous two months based on the parameters in the intermediate model plus the weighted average prices of cereal crops (wheat, barley, sorghum, and rice), and meat (beef, lamb, and pork) which are the main agricultural outputs of the MIA:

$$P_{W(m+1)}^T = f\left(P_{W(Avg.(m,m-1,m-2))}^T, P_{W(Avg.(m-1,m-2,m-3))}^T, SPI_{Avg.(m-1,m-2,m-3)}^T, A_{Avg.(m,m-1,m-2)}^T, A_{Avg.(m-1,m-2,m-3)}^T, A_{Avg.(m-2,m-3,m-4)}^T, P_{C(Avg.(m,m-1,m-2))}^T, P_{G(Avg.(m,m-1,m-2))}^T, P_{M(Avg.(m,m-1,m-2))}^T\right) \quad (3)$$

where:

M	Month;
T	Year;
Avg.	Average;
$P_{w(m+1)}$	Predicted water allocation price (A\$ ML^{-1}) for the next month;
$P_{w(Avg. (m, m-1, m-2))}$	Weighted average water allocation price (A\$ ML^{-1}) for the current month, last month and two months ago;
$P_{w(Avg. (m-1, m-2, m-3))}$	Weighted average water allocation price (A\$ ML^{-1}) for the last month, last two months, and three months ago;
$SPI_{Avg. (m-1, m-2, m-3)}$	Average standardized precipitation index (SPI) for the current month, last month and two months ago;
$A_{Avg. (m, m-1, m-2)}$	Average general security water volumetric allocation (percent) for the current month, last month and two months ago;
$A_{Avg. (m-1, m-2, m-3)}$	Average general security water volumetric allocation (percent) for the last month, two months ago and three months ago;
$A_{Avg. (m-2, m-3, m-4)}$	Average general security water volumetric allocation (percent) for two months ago, three months ago and four months ago;
$P_{c(Avg. (m, m-1, m-2))}$	Weighted average commodity price (A\$ $tonne^{-1}$) of cereal (c) crops for the current month, last month and two months ago (wheat, barley, sorghum, rice);
$P_{g(Avg. (m, m-1, m-2))}$	Weighted average grape (g) prices (A\$ $tonne^{-1}$) for the current month (m), last month and two months ago;
$P_{m(Avg. (m, m-1, m-2))}$	Weighted average meat (m) prices (cent kg^{-1}) for the current month, last month and two months ago (beef, lamb, pork).

Descriptive statistics for all variables are presented in Table S3.

2.3 Data sources

Time series data on water allocation trade covering the period from 1998 to 2015 were obtained from the *Water Exchange* (the MIL water allocation trade platform) and various annual and environmental reports from MIL (MIL, 2008–2015). Data for high and general security water volumetric allocation were obtained from MIL (2017) and the federal Department of Agriculture and Water Resources (2017).

Water use, and thereby water allocation demand, is a function of precipitation and evaporation, for which SPI—a normalized continuous rainfall variability function—is a proxy. The SPI was computed for four major regions in the study area (31.5°S – 36°S , 143.7°W – 149.5°W) from rainfall data for January 1999 to August 2015 obtained from the Australian Bureau of Meteorology (BOM, 2015). The index is based on statistical techniques and can quantify the degree of wetness and evaporation by comparing monthly rainfall totals with historical rainfall data (McKee et al., 1993). Data on commodity prices (see Supplementary Table S3) were obtained from the Australian Bureau of Agricultural and Resource Economics (ABARE, 2015).

Belsley collinearity diagnostics (Belsley et al. 1980) were used to assess the strength and sources of collinearity among variables in the multiple linear regression model; no significant correlations were identified.

2.4 Model Development: Hybrid Artificial Neural Network-Bayesian (ANN-B) modelling

Assuming the data are observations from a continuous probability distribution, the ANN-B model will begin by studying the distribution of the data in order to model their behaviour. According to the nature of ANN, the neural inputs are then processed by the likelihood function in Bayes' rule. If the data are represented by $X = (x_1, x_2, \dots, x_n)$ and the set of parameters θ determines the probability distributions of X , the probability densities of X can be presented as $P(x_i | \theta)$. The likelihood

function $L(\theta | X)$ is then the probability of the observed data X conditional on the values of parameter θ (MacKay, 1992; Robert, 2007):

$$L(\theta | X) = L(\theta | x_1, x_2, \dots, x_n) \propto P(x_1, x_2, \dots, x_n | \theta) = \prod_{i=1}^n P(x_i | \theta) \quad (4)$$

The prior distribution $P(\theta)$ is defined to express the parameter θ . Suppose the input signal X has the normal observation $X | \theta \sim N(\theta, \sigma^2)$, where standard deviation σ is known and the prior distribution for theta is $\theta \sim N(\mu, \tau^2)$. The posterior distribution for θ can be expanded via the normal probability density function:

$$f(\theta | \mu, \tau) = \frac{1}{\tau\sqrt{2\pi}} e^{-\frac{(\theta-\mu)^2}{2\tau^2}} \quad (5)$$

Bayes' theorem gives the posterior probability density function (pdf) for parameter θ as:

$$P(\theta | x_1, x_2, \dots, x_n) = \frac{P(x_1, x_2, \dots, x_n | \theta)P(\theta)}{P(x_1, x_2, \dots, x_n)} \propto L(\theta | x_1, x_2, \dots, x_n)P(\theta) \quad (6)$$

where P denotes the prior pdf of θ . The posterior distribution combines the prior function with the likelihood function (Figure 2).

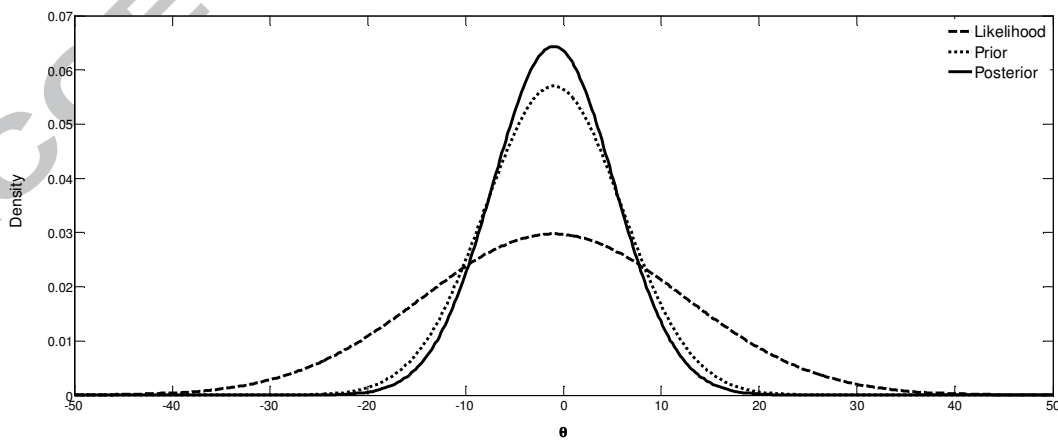


Figure 2: Prior, likelihood and posterior density functions of the fluctuation of allocation trading prices. Posterior probability is the product of prior probability and likelihood.

A Bayesian function can predict the value of an unknown quantity \mathcal{X}_{n+1} with respect to the posterior distribution of the parameters as:

$$P(x_{n+1} | x_1, x_2, \dots, x_n) = \int P(x_{n+1} | \theta) P(\theta | x_1, x_2, \dots, x_n) d\theta \quad (7)$$

The objective of this model is to predict the distribution of the target values y_{n+1} . The weights and biases are trained, based on a set of the maximum of likelihood values for the input data $X = (x_1, x_2, \dots, x_n)$ and associated targets $Y = (y_1, y_2, \dots, y_n)$. From equation (6), the predicted distribution of \hat{y}_{n+1} can be presented as:

$$P(\hat{y}_{n+1} | x_{n+1}, (x_1, y_1), \dots, (x_n, y_n)) = \int P(\hat{y}_{n+1} | x_{n+1}, \theta) P(\theta | (x_1, y_1), \dots, (x_n, y_n)) d\theta \quad (8)$$

2.5 Model training and sensitivity analysis

When the network was trained, the divide function was automatically accessed and the data were randomly divided into three subsets. The fraction of data placed in the training set, validation set, and test set were as follows:

- (i) a training set (train_ratio = 60%), used for computing the gradient and updating the network weights and biases;
- (ii) a validation set (validation_ratio = 20%) in which the error on the validation set was monitored during the training process; and
- (iii) a test set (test_ratio = 20%), used for testing the final solution in order to confirm the actual predictive power of the network.

The basic, intermediate and full model networks were trained through 1,000 iterations, where the mean squared error for both sub-samples decreased and then started to increase for the second/validation sub-sample, indicating that the network had learnt very effectively, conforming to the ANN and ANN-B primary principal of error minimization. When the training in Neural Networks was complete, the network performance could be used to check and determine if any changes needed to be made to the training process, the network architecture, or the data sets.

The models were also tested with regard to their sensitivity to the input variables (i.e. the relative impact of each input variable on water allocation price). Sensitivity analysis provided a key measure of the effect of an input value on the output value; hence, input variables with low sensitivity may be removed to decrease the network calculations as these will have little or no impact on the prediction result.

A nonlinear auto regressive model with an external input (ARX) was also used to predict the water allocation price over the time span of measured data to enable comparison and validation of the ANN and ANN-B models (Billings, 2013).

3. Results and Discussion

A total of 19,723 sub-daily water allocation market transactions, converted into monthly values, were used. Of these, 11,753 (60% of total observations) were used for model training, with no major problems encountered. The best performing networks for the basic, intermediate and full models are shown in Table 1; these were identified as those models with the lowest errors in the training, validation and testing processes (Best-perf., Best-vperf., Best-tperf., respectively). Training and testing errors were lowest in the ANN-B Full models compared with ANN models.

Table 1. Results for training, validation and testing of ANN and ANN-B models.

Item	Basic Model		Intermediate Model		Full Model	
	ANN	ANN-B	ANN	ANN-B	ANN	ANN-B
Best-perf.	0.45	0.54	0.20	0.25	0.17	0.01
Best-vperf.	0.07	0.05	0.10	0.15	0.09	0.07
Best-tpperf.	0.12	0.05	0.27	0.16	0.17	0.04

Perf. : performance; vperf.: validation performance; tperf.: testing performance.

Figure 3 shows the value of the performance function versus the iteration number of training, validation, and test performance. The best network results for the ANN models were found at the 12th, 3th and 4th iterations for the basic, intermediate and full models, respectively (Fig. 3 a, b, c). For the ANN-B models, the best network results were found at the 4th iteration for the basic model, 4th iteration for intermediate model and at 5th iteration for the full model (Fig. 3 d, e, f). In these figures, there are no major problems with the training. Validation and test curves were similar, and no overfitting occurred.

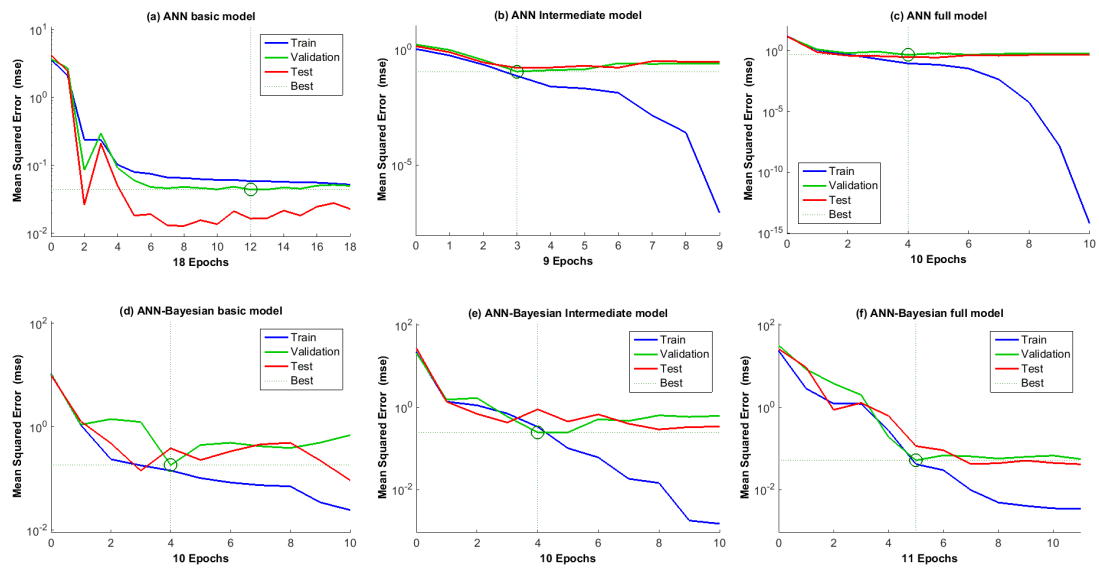


Figure 3: Validation performance results for the ANN basic (a), intermediate (b) and full (c) models and ANN-Bayesian basic (d), intermediate (e) and full (f) models.

3.1 Model validation

The validation of network performance was based on a regression of scatter plots of predicted versus observed water allocation trading prices, as shown in Figure 4. The regression coefficient ($0 \leq R \leq 1$) indicates the relationship between the actual water allocation price and the predicted water allocation price. The full ANN-B model showed better predicting performance, as reflected by the regression coefficients ($R_{Full} = 0.99$) between actual and model generated water allocation prices, than either the intermediate ($R_{Inter.} = 0.96$) or basic ($R_{Basic} = 0.93$) models. For the ANN model, regression coefficient values were $R_{Full} = 0.89$, $R_{Inter.} = 0.87$ and $R_{Basic} = 0.82$.

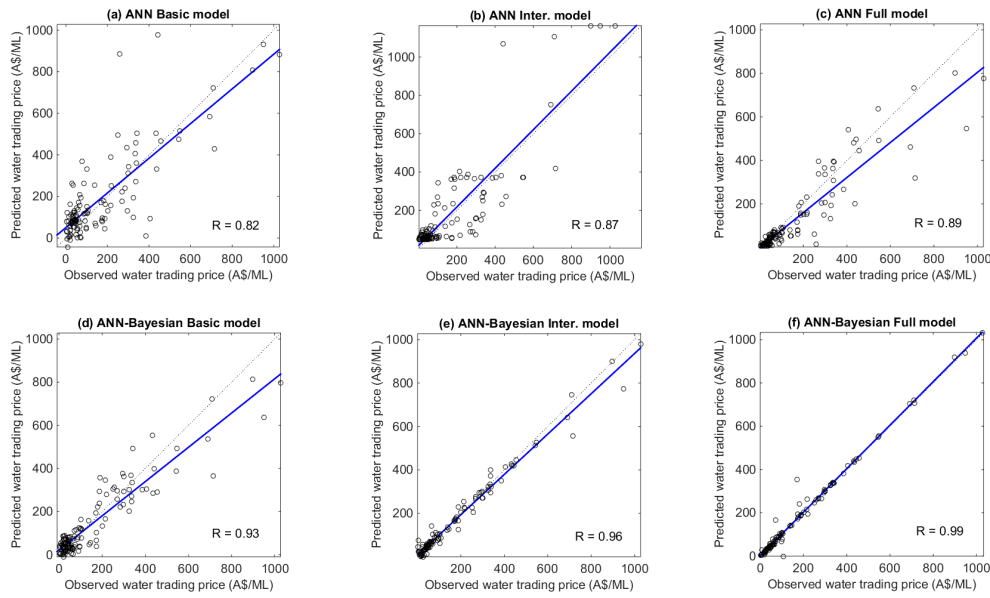


Figure 4: Regression of predicted water allocation price (network output) and the corresponding observed water allocation price for the basic, intermediate and full ANN (a–c) and ANN-B (d–f) models. (The solid line shows the best linear fit and the dashed line shows the perfect fit.)

The responses of the predicted water allocation prices for the time series are shown in Figure 5 (a–c) for the ANN model and 5 (d–f) for the ANN-B model. In these figures, errors are highest in the basic and intermediate ANN models, and lowest in the full ANN-B model. The better performance of the

full ANN-B model is mainly associated with the inclusion of water volumetric allocations and cereal and meat prices, which enabled water allocation price volatility to be better captured than in other models, especially during the period between 2006–07 and March 2009, when water allocation prices were very high due to extremely low seasonal water volumetric allocations in the MIL.

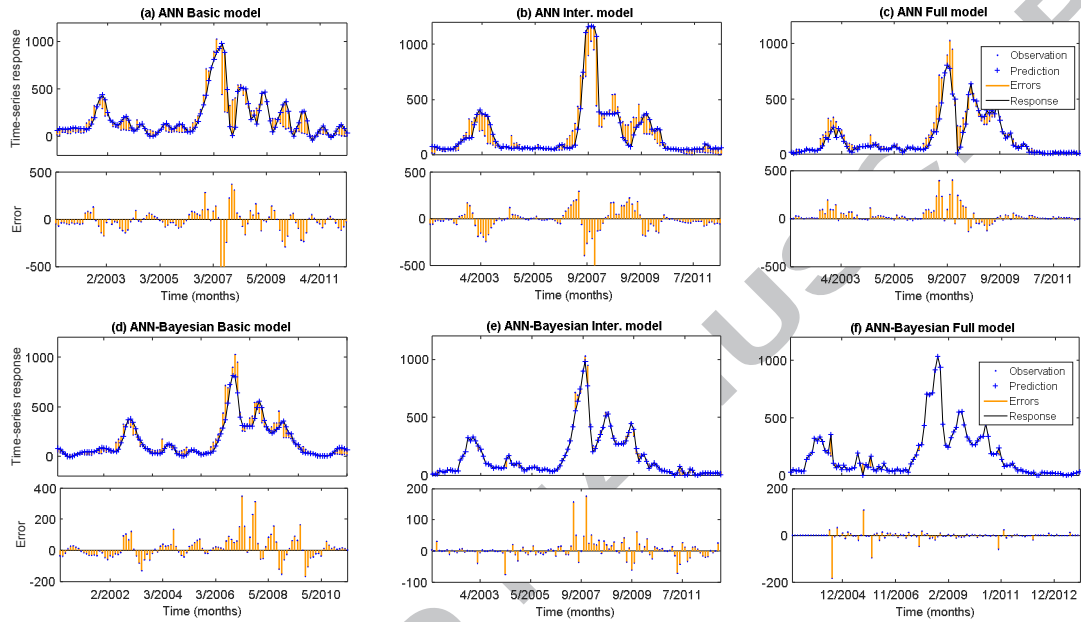


Figure 5: Time series responses for observed water allocation prices and predicted water allocation prices of various models. (Time scale on the x-axis may vary because data were randomly divided into three subsets when training the multilayer networks, as described in subsection 2.5)

3.2 Model testing

Overall, the models showed good predictive capabilities, with predicted water allocation prices close to actual water allocation prices in all six (basic, intermediate, and full ANN and ANN-B) models (Table 2). The full ANN-B model had the lowest minimum error, primarily due to the inclusion of more parameters than the basic or intermediate models. The full ANN-B model was also better able to forecast future water allocation prices with lower forecast error margins than the intermediate or basic ANN-B models across all months (Table 2, Figure 6). In all cases, the medians are roughly centered

between the quartiles indicating that the middle half of the errors are roughly symmetric and the error distributions are not skewed.

A nonlinear auto regressive model with an external input (ARX) was also considered in the case of the full generic model for comparison (Billings, 2013). Predicting with ANN-B model gave better results than predicting with the ARX model.

Table 2. Model statistics for ANN and ANN-B basic, intermediate and full models used to predict water allocation prices for September 1999 to May 2013 in the Murray Irrigation Area, Australia.

Item	Basic model		Intermediate model		Full model		Nonlinear ARX model
	ANN	ANN-B	ANN	ANN-B	ANN	ANN-B	
RMS	0.59	0.62	0.44	0.47	0.40	0.13	0.70
MAE	0.33	0.23	0.33	0.29	0.23	0.05	0.41
R	0.82	0.93	0.87	0.96	0.89	0.99	0.802

RMS: Root Mean Square; MAE: Mean Absolute Error.

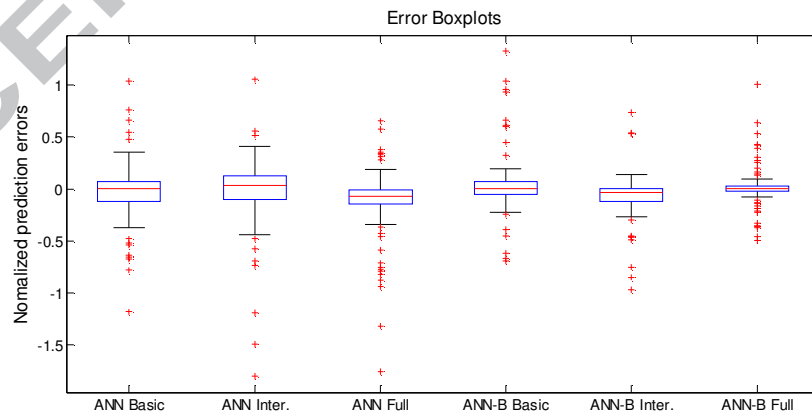


Figure 6: Error boxplots for the basic, intermediate and full ANN and ANN-B models.

3.3 Predicting water allocation prices

Network performance was assessed by comparing model outputs (prediction) with target (actual) water allocation prices in Figures 7(a, b, c) for ANN models, and 7(d, e, f) for ANN-B models. The ANN-B-model-generated predictions appear to more closely fit the actual data curves (Figure 7), indicating that, over the entire data set, ANN-B models show greater agreement between actual and predicted prices, and were therefore better able to predict prices. Overall, the full ANN-B model showed better prediction ability due to the inclusion of more parameters in the model which capture the volatility in prices during the 2002–03 drought, when volumetric allocations were very low, and 2006–07, when initial water allocations up to March 2007 were close to zero.

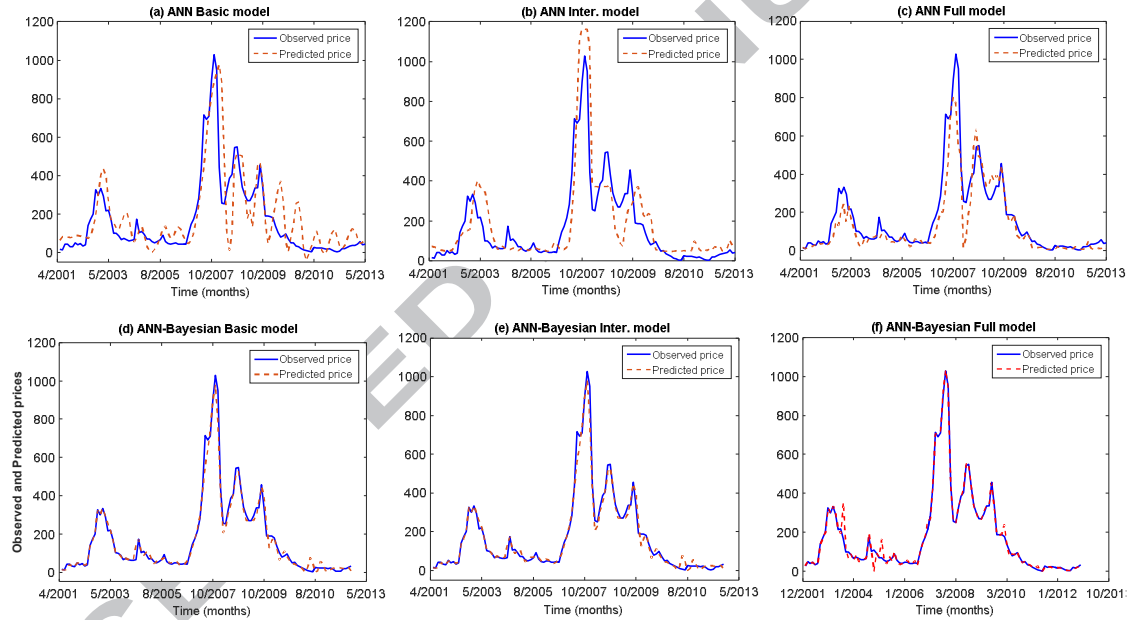


Figure 7: Observed and monthly predicted water allocation prices (model output) for basic, intermediate and full ANN and ANN-B models.

The results from the ANN-B Full, ANN-B Intermediate and ANN-B Basic models were tested by predicting water allocation prices. Table 3 shows the overall performance of the Basic, Intermediate and Full models in a real setting from February 2006 to December 2006, excluding winter months (May–July 2006) when there was little or no water allocation trading; this period was during the ‘Millennium drought’ (1996–2010) when water allocation prices were far higher than in previous

years. The results from the ANN-B Full model has smaller errors than either the ANN-B Intermediate or ANN-B Basic models (Table 3); overall the error range (1.53%–12.08%) highlights the superior capabilities of the ANN-B models.

Table 3: Observed prices, predicted prices and model errors for Basic, Intermediate and Full ANN-B forecast water allocation prices for the eight month period from February to December 2006 during the Millennium Drought in Australia's Murray-Darling Basin.

Year	Observed	Full model		Inter. Model		Basic model	
2006	price						
Months	(\$/ML)	Predicted price	Error (%)	Predicted price	Error (%)	Predicted price	Error (%)
February 06	41.66	43.63	-4.75	47.04	-12.93	45.78	-9.90
March 06	41.21	39.15	4.99	43.09	-4.57	40.19	2.45
April 06	43.79	42.02	4.04	45.26	-3.36	42.67	2.55
August 06	144.69	139.77	3.39	138.13	4.52	148.52	-2.65
September 06	174.27	182.93	-3.12	177.40	-2.83	172.52	1.01
October 06	215.95	221.98	-2.28	217.03	-4.02	208.64	3.39
November 06	283.41	285.58	5.67	302.73	-12.08	270.11	4.69
December 06	435.84	433.86	-1.53	427.30	-7.30	398.22	8.63

In Table 3, the observed and predicted price data are presented for the normal period (February to April 2006) and the extreme period (August to December 2006). The models show good predictive capabilities within the training range using unsupervised learning from February 2006 through to December 2006, when predicted water allocation prices were close to actual water allocation prices. In the ANN-B Full model, the maximum error (5.67%) occurs when the price increased 24% from AU\$215.95/ML in October to AU\$283.41/ML in November.

3.4 Network sensitivity

Finally, we examined the sensitivity values of the model outputs to each input variable varied across input levels (Table 4). For example, water allocation prices were most influential in the basic, intermediate and full ANN models and in the basic and intermediate ANN-B models. However, meat and cereal prices were the most significant parameters impacting the predicted water allocation price in the full ANN-B model. The full ANN-B model was most sensitive to the water allocation price and meat and cereal prices (Table 4).

Table 4. Summary of parameter contributions for all models

Performance Type	$C(x_i) \times 100\%$			$C(x_i) \times 100\%$		
	ANN Model			ANN-B Model		
	Basic (%)	Inter. (%)	Full (%)	Basic (%)	Inter. (%)	Full (%)
Water Allocation Trading Price ($Pw(m-1)$)	25.82	20.10	34.56	18.68	20.44	11.95
Water Allocation Trading Price ($Pw(m-2)$)	35.90	30.05	28.58	37.22	25.40	12.22
Water Allocation Trading Price ($Pw(m-3)$)	38.28	42.12	21.49	44.10	28.12	14.70
General Security Water Allocation (m)	--	0.98	1.00	--	0.15	14.65
General Security Water Allocation ($m-1$)	--	0.48	0.53	--	0.19	0.15
General Security Water Allocation ($m-2$)	--	2.07	1.72	--	0.27	0.18
General Security Water Allocation ($m-3$)	--	4.05	3.11	--	0.33	0.19

Standard Precipitation Index (<i>SPI</i>)	--	0.15	0.05	--	25.10	12.06
Cereal price (<i>m</i>) ^a	--	--	6.48	--	--	14.78
Meat price (<i>m</i>) ^b	--	--	2.48	--	--	19.12
Total/constant	100	100	100	100	100	100

^aCereal includes wheat, barley, sorghum and rice

^bMeat includes beef, lamb and pork

-- Not applicable

4. Conclusions and implications

Water scarcity is a key constraint to profitable agriculture. Water markets can reallocate water from low to high valued agricultural uses enabling gains in efficiency and overall productivity (White *et al.*, 2006; Qureshi *et al.*, 2013; An-Vo *et al.* 2015). In periods of scarcity, volumetric water allocations and water allocation prices will remain uncertain, hindering efficient decision-making regarding land and water management, investments into inputs, and potential national, regional and individual gains from trade. Continued drought can exacerbate this situation, and under such conditions water buyers and sellers will likely face high levels of water allocation price uncertainty in markets. The ability to forecast water allocation prices (e.g. seasonal allocation prices) could enable irrigators to make more informed decisions on water allocation and natural resource management to help boost returns to their investments by more effectively using increasingly scarce and expensive water supplies to gain from trade.

This paper presents a novel hybrid Artificial Neural Network-Bayesian (ANN-B) model developed to better predict water allocation prices in the Murray Irrigation Area in Australia. The results indicate that both ANN and ANN-B modelling approaches can be successfully used for time series prediction by simulating complex and non-linear processes which are often not adequately addressed by conventional regression or time series models. While ANN approaches are often used for such purposes, our modelling results also show that water allocation prices can be more successfully

predicted ($R=0.99$) using an ANN-B approach, with simulation results from the ANN-B models found to be more accurate than those of the standard ANN models across a range of data inputs. The results indicate that current water allocation prices, general water security volumetric allocations and other data such as cereal and meat prices are significant determinants of future water allocation prices.

Application of the ANN-B model in a real world setting indicates the potential for good water allocation price prediction capability within the training range of the model. ANN-B models will be considered and improved for further commercialized applications such as spreadsheets and real time data acquisition to enhance their functionality. The applications can also be useful for addressing a range of issues such as water allocation price risk, irrigation infrastructure investments and asset management decisions; contingency planning for drought; natural resource management planning; and regional development planning. Further, the framework could be used to forecast volumetric allocations or water allocation prices in other irrigation districts to generate valuable information. With continued commitment by policy makers to the water allocation market, improved capacity of agricultural water users in the timely selection of annual commodities and/or risk management arrangements with more accurate water allocation market price predicting in water markets should create greater economic and water use efficiency.

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Key Points

- Artificial Neural Network (ANN) approaches were used to model and predict water trading prices in the Murry Irrigation area, Australia.
- Prices forecast using hybrid ANN-Bayesian modelling showed greater agreement with actual water prices.
- Water security allocations, cereal and meat prices were significant determinants of future water trading prices.